An Improved Integrated Intensity-Hue-Saturation with Stationary Wavelet Transform Multi-sensor Image Fusion Approach

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Abstract—**Image fusion aims to retrieve information data from a set of multiple images into a composite output image. Pan-sharpen is the method of combining a high spatial resolution panchromatic (PAN) image and a high spectral resolution multispectral (MS) data of the same scene. It is not only beneficial for enhancing the spatial contents but also to preserve its spectral quality to be more useful for interpretation. Intensity-Hue-Saturation (IHS) transform is the most commonly performed method of image fusion, but it causes some spectral distortion. A proposed hybrid approach applies IHS fusion with a Stationary Wavelet Transform (SWT) because the recent usually preserves the color information via multilevel decomposition. By using different fusion rules, for combining the corresponding approximation and details coefficients obtained from wavelet decompositions, a coefficient combining and activity level measurement based fusion rules are executed. The main characteristic of the composite platform is utilizing the features of the combined algorithms with different fusion rules into a single image. The fusion results are evaluated and compared with results by conventional fusion techniques. Choosing of the optimum fusion rule counts on the type of imageries to be fused and depending upon the application. Visual inspection and quantitative analysis demonstrate that successful results among the different fusion methods.**

Keywords— ***Multi-sensor image fusion; PCA; IHS; DWT; SWT; Filter mask***

I. INTRODUCTION

Multi-sensor data fusion is a challenging research in many remote sensing (RS) image processing applications because of the different characteristics of remotely sensed data acquired from multisensory [1]. For satellite RS applications, Image fusion process is the most popular approach of combining a single band PAN or synthetic aperture radar (SAR) image with high spatial resolution and MS (color) data with a lower spatial resolution in order to create a resultant unique image with more significant and accurate information than the individual sources [2]. The fusion techniques should ensure that all spatial details and spectral characteristics in the original images are injected into the fused image, without introducing inconsistencies or any artifacts, which may affect the quality of the output image [3]. Therefore, the new fused image has to be more informative and spatially better than any of the individual images and doesn't lead to wrong diagnosis.

According to the fusion of multi-sensor images, there is generally a compromising between getting a good image, spatially and spectrally, which resulting in information loss [4]. In general, fusion takes place at three different levels, they are pixel level (lowest level), feature level (intermediate level) and decision level (high-level) fusion. In this study, a data/pixel level based image fusion is presented in order to perform a fusion process, generating a single complementary image, containing an extra truthful description than any of the single sources [5]. The most common approaches for image fusion are the band substitution methods including the Intensity-Hue-Saturation (IHS) and Principal Components Analysis (PCA), etc. Those approaches; are generally known as component substitution (CS) algorithms, this group of methods generates a high spectral distortion to the original color information [6]. Contrarily, the multi-resolution approach has been proposed for image fusion which introduces the multi-scale decomposition (MSD) such as the basic Discrete Wavelet Transform (DWT) [21, 23]. Although the wavelet analysis is an interesting tool which can avoid information distortion and getting better performance for image fusion. the main disadvantage of DWT is a shift-variant. Therefore, this disadvantage can be overcome by using a wavelet technique which is shift-invariant wavelets is called Stationary Wavelet Transform (SWT) [1-21-22].

However, many comparisons have showed that IHS fusion results present a good color-feature integration, but there is a big color distortion. Wavelet based fusion methods demonstrates color information preserving better than does the IHS. Researchers have developed hybrid fusion algorithms, integrating two or more fusion techniques in one framework to solve the color distortion problem. Several fusion rules have been submitted for image fusion which is either activity-level measurement method or coefficient combining method [19-20]. Two methods are being discussed.

This paper proposed a novel hybrid IHS-SWT based image fusion algorithm, integrating both coefficient combining Based; choose-mean for approximation coefficients and activity level measurement; Window Based Activity (WBA) fusion rules such as High-Pass (HP), Low-Pass (LP) and Weighted Average (WA) filter masking for details coefficients in an individual single fused images.

For estimation the quality of fused products, a qualitative and quantitative evaluation is presented. Results demonstrate that the proposed integrated algorithm improves the quality of Quick Bird fused images in comparison of the traditional methods.

The paper is summarized as follows: Section II gives a brief review about the classical image fusion techniques. Section III is devoted to the proposed hybrid algorithm. Section IV deals with the experimental results and describes quality metrics for evaluation. Finally, conclusions including discussion are recapitulated in section V.

II. CONVENTIONAL FUSION TECHNIQUES

High resolution PAN and coarser MS imageries have to be pre-processed before pan-sharpening. Pre-processing may involve Image Registration (IR) to make input images aligned and registered which is a prerequisite to apply fusion techniques. It is followed by Resampling (RS) of multispectral image to that of PAN image. Histogram matching is performed before applying pan-sharpen. In this step, histogram matching is utilized for equalization standard deviation and mean to make the spectral distortion less for both images and for solving the problem of non-linear differences between them [16]. The next section describes some of the traditional image fusion Methods for satellite images.

A. Component Substitution (CS)Methods

The principal of CS (also called projection substitution) techniques is to project the original MS bands using a transformation in different components. Then, one of the resulting components which contains the spatial information is replaced by the higher spatial resolution pan imagery. The higher correlation between both input data, the less distortion of data. Thus, by applying the inverse transform, the fused image is produced [29].

1) Intensity-hue-saturation (IHS) Fusion method:

Intensity, hue and saturation technique is a standard procedure in pan-sharpening approaches in the CS category. To understand IHS, the three primary bands (red, green and blue) of the MS imagery have to be converted into (IHS) space. In IHS color space, the spatial details are enclosed in intensity component, while the spectral information of a color image mainly lies in hue and saturation. The histogram of the Pan imagery is usually matched to the intensity (I) band before the replacement in order to get a better fusion quality. Afterwards, the (I) component is substituted by the high-resolution panchromatic imagery then the histogram matched Pan is gathered with H and S bands and finally applying a reverse transformation from IHS to RGB space, generating a high spatial color image. Fig. 1. Describes IHS method [30-31].

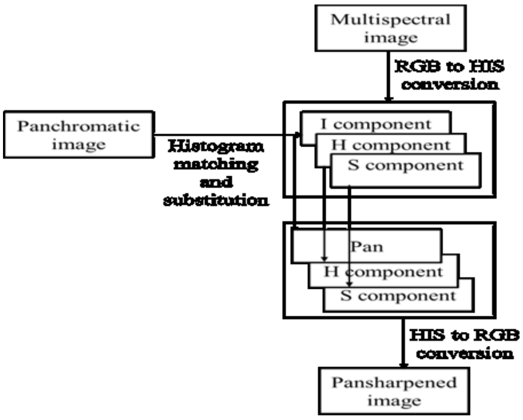


Fig. 1. *Image Fusion with the IHS method.*

If the correlation between PAN and MS images is very high, then the fused image has better spatial resolution for analysis. The main disadvantage of CS based techniques is that significant spectral distortion which is also called radiometric distortion [11].

B. Multi-Resolution analysis (MRA)

The MRA methods include Laplacian pyramid and the wavelet transform is based on MSD of the high spatial resolution imagery to extract the spatial details and then transferring into the color image. Particularly, The MRA fusion approaches usually give superior performance in terms of reducing the spectral distortion compared to CS based methods [12, 32].

1) Stationary Wavelet Transform:

Stationary wavelet transform (SWT) is an approximation of the classical DWT. Whereas, SWT is slightly different from the shift-variant DWT, also known as UN decimated DWT or shift-invariant because it is carried out by suppressing the step of down sampling at each scale instead of up-sampling the filters at each scale in the DWT computation. In SWT, filter coefficients are modified by zeroes insertion. [23-33].

Standard DWT is shift-variant which causes artifacts in the fused images, therefore it can be avoided by applying SWT [25]. The 2D-SWT solves the decimation problem by applying modified High pass and low pass filters at each level without any decimation. SWT produces two sequences at the next stage. The two new sequences are having same length as that of the source image. SWT is schematically visualized in Fig. 2. [27].

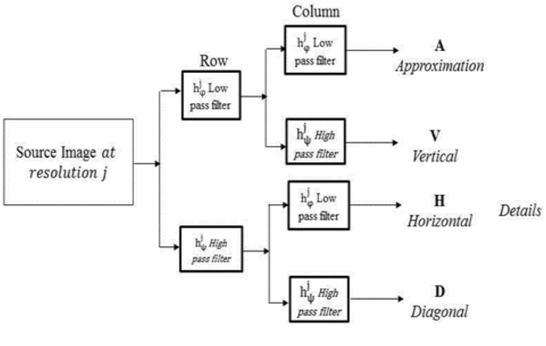

Column
Row
Source Image at resolution j
h_{φ}^{j} Low pass filter
h_{ψ}^{j} High pass filter
h_{φ}^{j} Low pass filter
h_{ψ}^{j} High pass filter
h_{φ}^{j} Low pass filter
h_{ψ}^{j} High pass filter
A
Approximation
V
Vertical
H
Horizontal
D
Diagonal
Details

Fig. 2. *2-D Stationart Wavelet Transform.*

In order to implement SWT on an image, the dimensions of the image should be integer multiples of 2j , where j represents the number of wavelet decomposition levels applied. The LP and HP filters employed for wavelet decomposition at j-th scale are represented by the symbols h^j_Φ and h^j_Ψ respectively. The outputs of LP and HP filters are corresponding to the approximations (low frequency) and details (high frequency) sub images of the input image respectively. Therefore, the SWT produces four sub-images at a lower scale; Approximation (A), Horizontal (H), Vertical (V) and diagonal (D).

a) Fusion Rules.

Image fusion rules can be defined by the strategy of the fusion, which determines how the different coefficients will be combined [18]. Image fusion rules are divided into two main parts, coefficient combining method and activity-level measurement method. Choosing MAX or MIN, or MEAN fusion rules are the most popular coefficient combining methods. Whereas, three methods are generally for adopting the activity level of a MSD; coefficient-based (CB), window-based (WB) and region-based (RB) which requires a good region segmentation. Therefore, it is ineffective for some applications [8-9]. Window based activity level measurement (WBA) fusion rule considered that there is a high correlation among neighboring pixels, for example, 3x3 or 5x5 windows. Many options of WBA, such as a weighted average (WA-WBA), rank filter and the space frequency [9, 19].

According to these mathematical fusion rules, the decomposed wavelet coefficients extracted from the source images are merged to form fused wavelet coefficients before the backward wavelet transform. Test data are decomposed using multi-level 2-D SWT. Approximation coefficients (APX) are subjected to mean selection as a pixel based fusion rule.

Where A (i, j) and B (i, j) are the input images and M (i, j) is the output fused approximation sub image. While 3x3 square high-pass, low-pass and weighted average filter masks are applied to detail coefficients (DET) as a WB fusion rules, individually, as follows:

$$\text{High-pass filter kernel} = \begin{vmatrix} 0 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 0 \end{vmatrix} \qquad (1)$$

$$\text{Low-pass filter kernel} = \frac{1}{9}\begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{vmatrix} \qquad (2)$$

$$\text{Weighted average filter kernel} = \frac{1}{16}\begin{vmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{vmatrix} \qquad (3)$$

III. PROPOSED ALGORITHM

As discussed before, exploiting the wavelet analysis integrated with IHS Transform is to enhance the advantages and overcome the limitations of each technique. Combining different fusion rules, leads to developing hybrid algorithm, integrates the merits of the different fusion rules for fusing the decomposed low and high frequency sub images. Fig. 3. Shows the flow chart of the algorithm that divided into three main procedures:

(I) IHS Transform.
(II) Multi-level 2-D Stationary Wavelet Transform.
(III) Applying the different fusion rules for combining low and high frequency coefficients of wavelet decomposition.

1) Algorithm:

Before the image fusion, the MS image are co-registered to the corresponding Pan image and resampled using Cubic Convolution to the pixel sizes of the Pan image. Cubic Convolution method reduces the stepped effect which produced by the Nearest Neighbor method .it takes more neighboring cells compared to bilinear resampling and it makes pixels looking smooth [34].

We have summarized the proposed algorithm steps as follows:

1. Transfer the MS image from (RGB) color space into the IHS space (Forward IHS transform).
2. PAN imagery is histogram matched with Intensity (I) component and generate a new pan image (Matched Pan).
3. Perform independent multi-level 2-D SWT of the Matched Pan image and Intensity (I) to the level L to obtain the approximation (LL^L) and the detail (LH^1 ,HL^1 ,HH^1) coefficients up to level 2 of decomposition where l = 1, 2,…, L.
4. Choosing mean pixel based algorithm for approximations (LL^L) by choosing the average valued pixels from the APX of the Matched Pan and I images.

   $$LL^L_f = \text{mean}\ ((LL^L_I (i, j)), (LL^L_P (i, j)) \qquad (4)$$

   Here LL^L_f is the fused and LL^L_I and LL^L_P are the approximations coefficients, i and j represent the positions of the sub-images pixels.

5. Based on filter mask, A 3X3 window is subjected to the DET sub-images is applied.
6. Perform window based fusion rule of detail coefficients by using three different square masks of 3X3 filters. The masked coefficients are added from each sub-band as below.

   $$LH^l_f = \text{mask}\ (LH^l_I) + \text{mask}\ (LH^l_P) \qquad (5)$$

   $$HL^l_f = \text{mask}\ (HL^l_I) + \text{mask}\ (HL^l_P) \qquad (6)$$

   $$HH^l_f = \text{mask}\ (HH^l_I) + \text{mask}\ (HH^l_P) \qquad (7)$$

   Where,
   LH^l_I, LH^l_P HL^l_I, HL^l_P, HH^l_I, HH^l_P are the vertical, horizontal and diagonal high frequencies respectively. LH^l_f HL^l_f, HH^l_f are the fused detail sub-bands respectively. LL^L_f is the fused APX through mean rules and LH^l_f, HL^l_f, HH^l_f are the vertical, horizontal and diagonal DET by applying the mask (WB) fusion rules for l =1,2,...,L.
7. By concatenating the output fused approximation and detailed coefficients, the fused result is reconstructed by inverse stationary wavelet transform (ISWT)

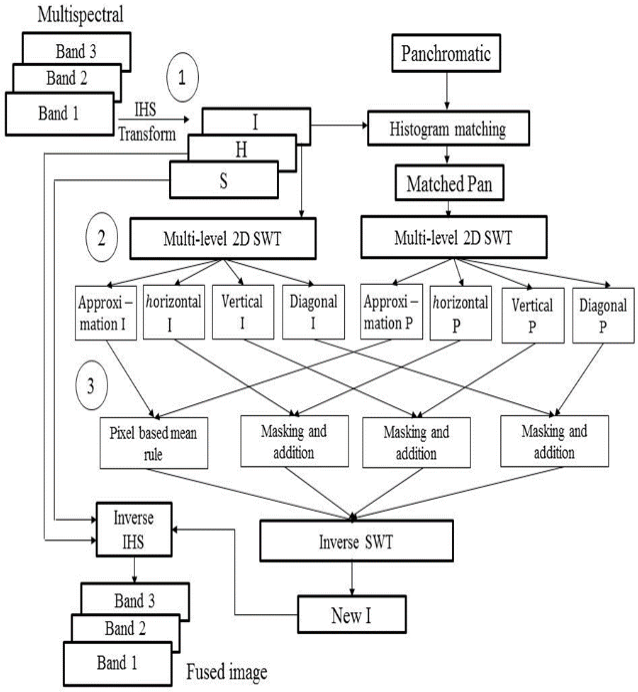


Fig. 3. *HIS-SWT Flow chart fusion algorithm*.

2) *Quality Metrics:*

However, neither qualitative nor quantitative evaluation alone will bring out satisfied results [15, 35]. Image fusion performance can be studied qualitatively by visual inspection of fusion results and quantitatively is done by statistically calculating and analyzing the assessment of image quality indexes as follows:

Peak Signal-to-Noise Ratio (PSNR) = $10\log_{10}\left(\frac{\mathrm{Max}^2}{\mathrm{MSE}}\right)$ (8)

Where,

Max is the maximum pixel value of the given image.

MSE is the mean square error. A higher PSNR value implies higher quality.

Consider a (i, j) represents original panchromatic imagery, g (i, j, k) denotes the original multispectral imagery with resampled no of bands k to be the same size as the PAN image. While f (i, j, k) is the fused image with size M and N respectively. Root Mean Square Error (RMSE) is calculated as:

$$\mathrm{RMSE} = \sqrt{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(f(i,j,k)-g(i,j,k))^2/MN} \qquad (9)$$

The spectral correlation coefficient (CC) is an index of similarity between the original MS and the fused images. The more closely of the CC to unity, identical the images will be.

$$\mathrm{CC}\,(f,g) = \frac{\sum_{i,j}[(f(i,j,k)-\bar{f})(g(i,j,k)-\bar{g})]}{\sqrt{\sum_{i,j}(f(i,j,k)-\bar{f})^2\sum_{i,j}(g(i,j,k)-\bar{g})^2}} \qquad (10)$$

The Entropy is the index of the richness of information content of image:

$$\text{Entropy (E)} = -\sum_{i=0}^{255} f_i \log_2 f_i \qquad (11)$$

The spatial quality is assessed by High pass filtering which is one of spatial indexes that can reflect the spatial fidelity of fused images as follows:

$$\text{Mask} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \qquad (12)$$

The correlation coefficient between the filtered PAN imagery and filtered merged results is used as an index of the spatial quality because most of spatial details are existed in the domain of high frequency [29].

IV. EXIPERMENTAL RESULTS AND EVALUATION

Input data consist of co-registered Quick bird PAN image which is rendered as gray image and natural color MS image of ground spacing 0.6 and 2.4 meter with size of 512×512 pixels for PAN image and 128×128 pixels for MS image. In Fig. 4, (a) is the high-resolution PAN imagery. (b), (c), (d) are the three primary colors (red, green and blue) of the MS imagery and (e) is the color image.

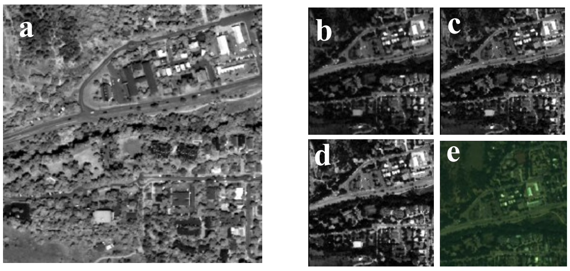
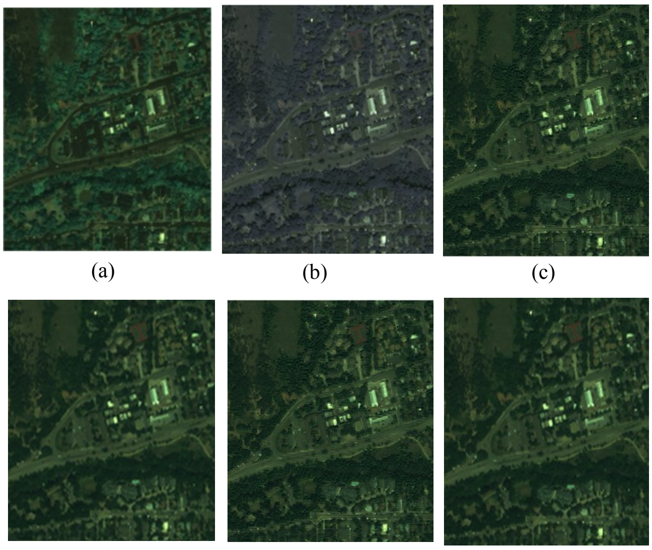


Fig. 4. *Original PAN and MS images*.

The tested methods include IHS, PCA, Standard 2D-DWT, multi-level 2D SWT, IHS-DWT, and the proposed IHS-SWT image fusion approaches as shown in Fig. 5.


(a) (b) (c)

(d) (e) (f)

Fig. 5. Fusion results obtained by different techniques: (a) Image Fusion by IHS. (b) Image Fusion by PCA. (c) Image Fusion by DWT. (d) Image Fusion by SWT. (e) Image Fusion by IHS-DWT. (f) Image Fusion by IHS-SWT.

Fig. 5. Shows the different fused images using different pan-sharpen methods, as shown in above figures, a bit of color distortion has appeared in the fused image obtained by IHS method. And also, a significant spectral distortion is found in the fused image by using PCA. Although, the other fusion results are perceptually good, they have some spatial and spectral distortions, which are represented statistically in table I. The integrated IHS-SWT fusion method has the lowest MSE values and then the highest PSNR values. Despite the spectral quality is perceptually good, the edges are not well distinguishable.

Note that The integrated IHS-SWT pan-sharpening method has also been carried out using different sets of fusion rules between the APX and DET coefficients i.e. Choose Max (CM)-WA,CM-LPF, CM-HPF, MEAN-WA, WA-MEAN, WA-CM,LPF-CM, HPF-CM. Results are evaluated for all possible combination methods for APX and DET coefficients.

Fig. 6. Shows the output Results of using different sets of fusion rules for (APX, DET) coefficients. Table III presents the values of quality metrics for different set of fusion rules for APX and DET coefficients.

TABLE I. Spectral assessment between image fusion techniques.

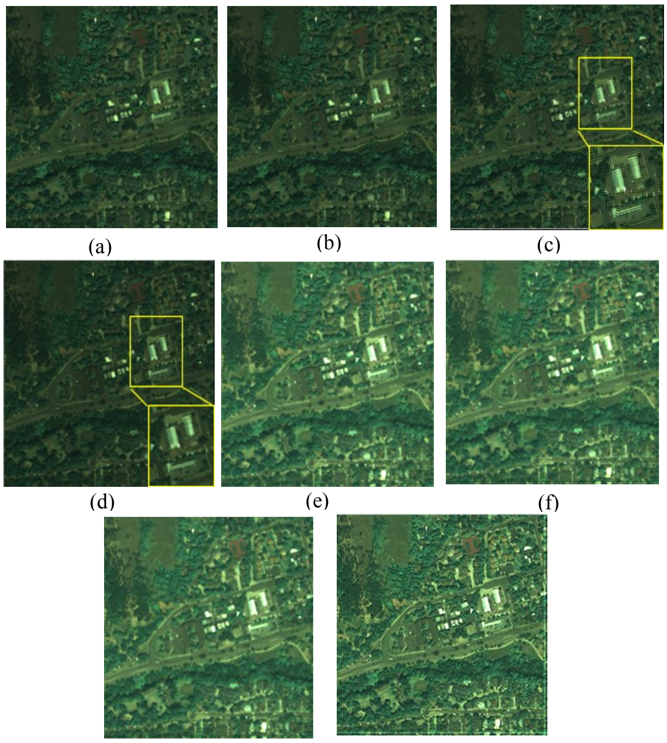
Algorithm	**E**			**Spectral CC**			**MSE**			**PSNR**		
	B3	B2	B1	B3	B2	B1	B3	B2	B1	B3	B2	B1
IHS	5.3	6	5.6	0.37	0.49	0.7	0.0007	0.0024	0.0018	79	74	75
PCA	5.64	5.84	5.77	0.6	0.9	0.8	0.0014	0.0004	0.003	76	81	73
DWT	5.4	6.2	6.1	0.8	0.8	0..8	0.0007	0.0005	0.0005	79	80	80
SWT	5.2	6	6	0.87	0.87	0.87	0.0006	0.0005	0.0005	80	80	80
IHS-DWT	5.5	6.3	6	0.83	0.87	0.92	0.0005	0.0006	0.0006	80	79	79
IHS-SWT	**5.2**	**6.1**	**5.9**	**0.88**	**0.96**	**0.98**	**0.0004**	**0.0001**	**0.0004**	**82**	**85**	**82**

Table I presents the comparison between the spectral assessment of the fused results according to the different standard (standalone) approaches ; IHS, PCA, DWT and SWT and the hybrid fusion approaches; IHS-DWT and IHS-SWT, using different quality metrics at each band (B3, B2 and B1) which represent the spectral bands (R,G and B). Quantitative analysis in table I shows that the hybrid IHS-SWT algorithm over performs the other methods in terms of values of the spectral quality metrics; E, CC, MSE and PSNR.

Table II presents the values of the spatial CC between the original pan image and the different fused results obtained from the fusion techniques. It shows that the hybrid IHS-SWT results are not as high as compared to those obtained by applying other methods, such as PCA but still sufficient.

TABLE II. Spatial assessment between image fusion techniques.

Algorithm	**Spatial CC**		
	B3	B2	B1
IHS	0.86	0.87	0.85
PCA	0.9	0.9	0.9
DWT	0.7	0.7	0.7
SWT	0.7	0.74	0.7
IHS-DWT	0.7	0.73	0.7
IHS-SWT	**0.75**	**0.76**	**0.74**



(a) (b) (c)

(d) (e) (f)

(g) (h)

Fig. 6. Results of pan-sharpening using different sets of fusion rules (fusion rule for APX, fusion rule for DET).

TABLE III. Spectral assessment between image fusion techniques combining different fusion rules (APX, DET).

Fusion rules	E			CC			MSE			PSNR		
	B3	B2	B1	B3	B2	B1	B3	B2	B1	B3	B2	B1
CM, WA	5.28	6.1	5.9	0.76	0.82	0.93	0.0004	0.001	0.001	81	77	77
CM, LPF	5.2	6.1	5.9	0.76	0.8	0.9	0.0004	0.001	0.001	81	77	77
CM, HPF	5.8	6.6	6.1	0.55	0.63	0.79	0.001	0.002	0.001	77	74	75
MEAN, WA	**4.8**	**5.8**	**5.6**	**0.8**	**0.86**	**0.9**	**0.0003**	**0.0005**	**0.0008**	**83**	**80.5**	**79**
WA, MEAN	5.7	6.7	6.6	0.83	0.87	0.94	0.008	0.01	0.007	69	65	69
WA, CM	5.7	6.7	6.6	0.8	0.87	0.94	0.0081	0.018	0.007	69	65	69
LPF, CM	5.7	6.69	6.62	0.89	0.84	0.76	0.0081	0.018	0.007	69	65.5	69
HPF, CM	6.3	7	6.8	0.7	0.78	0.88	0.01	0.02	0.009	68	64	68

As illustrated in Fig. 6. The results based on merging the coefficient combining and window based fusion rules. By adopting the MEAN-WA fusion rule which displays a good spectral quality and retains the boundary edges and the structural details without any inconsistencies to the fused image. Also MSE and PSNR values over perform the other values of different combinations.

Using MEAN-WA fusion rule shows the highest values of the SCC compared with the other different combinations as shown in table IV. Adopting HP filter helps in improving the features of salient edges, but it causes some spectral distortions. Whereas, averaging or low-pass filter removes noise by taking the average values of window that surrounding the center pixel and weighted average filter has a less Blurring effect compared to Average filter.

TABLE IV. Spatial assessment between image fusion techniques combining different fusion rules (APX, DET).

Fusion rules	Spatial CC		
	B3	B2	B1
CM, WA	0.73	0.74	0.7
CM, LPF	0.56	0.57	0.55
CM, HPF	0.76	0.76	0.75
MEAN, WA	**0.8**	**0.8**	**0.755**
WA, MEAN	0.79	0.8	0.75
WA, CM	0.77	0.78	0.72
LPF, CM	0.75	0.76	0.7
HPF, CM	0.76	0.76	0.73

V. CONCLUSION

In this study, the work done helps in explaining the principles for further research in image fusion by wavelet transform that implements a shift-invariant SWT and preserves the spectral information via multilevel decomposition, integrating with IHS fusion algorithm and combining two different types of fusion rules in a resultant image. In addition, the IHS-SWT hybrid algorithm discussed provides promising results spectrally and spatially simultaneously than other methods, which may not have always a good detection of features.

The proposed architecture uses two different methods of fusion rules, choosing mean is a better choice for combining the approximations. Furthermore, applying window based fusion rules for details. The changes in performance of the applied fusion rules for test images clarify that the choosing of the most optimum fusion rule counts on the type of imageries to be fused. It provides using different masks for fusion, depending upon the application.

REFERENCES

[1] Han, N., Hu, J., Zhang, W., & Liu, X. (2010, October). Multi-band à trous wavelet transform for multisensor image fusion. In 2010 3rd International Congress on Image and Signal Processing (Vol. 5, pp. 2207-2211). IEEE.

[2] Hong, G. H. G., & Zhang, Y. Z. Y. (2003, May). High resolution image fusion based on wavelet and IHS transformations. In 2003 2nd GRSS/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas (pp. 99-104). IEEE.

[3] Gungor, O., & Shan, J. (2004, July). Evaluation of satellite image fusion using wavelet transform. In proceedings of 20th Congress ISPRS "Geo-Imagery Bridging Continents (pp. 12-13).

[4] Sasikala, M., & Kumaravel, N. (2007). A comparative analysis of feature based image fusion methods. Information Technology Journal, 6(8), 1224-1230.

[5] Naidu, V. P. S., & Raol, J. R. (2008). Pixel-level image fusion using wavelets and principal component analysis. Defence Science Journal, 58(3), 338-352.

[6] Chavez, P., Sides, S. C., & Anderson, J. A. (1991). Comparison of three different methods to merge multiresolution and multispectral data- Landsat TM and SPOT panchromatic. Photogrammetric Engineering and remote sensing, 57(3), 295-303.

[7] Zhang, Y., & Hong, G. (2005, May). A wavelet integrated image fusion approach for target detection in very high resolution satellite imagery. In Signal Processing, Sensor Fusion, and Target Recognition XIV (Vol. 5809, pp. 330-341). International Society for Optics and Photonics.

[8] Kahraman, S., & Ertürk, A. (2018). Review and Performance Comparison of Pansharpening Algorithms for RASAT Images. Electrica, 18(1), 109-120.

[9] Huang, S. G. (2010). Wavelet for image fusion. Graduate Institute of Communication Engineering and Department of Electrical Engineering, National Taiwan University.

[10] Chavez, P., Sides, S. C., & Anderson, J. A. (1991). Comparison of three different methods to merge multiresolution and multispectral data- Landsat TM and SPOT panchromatic. Photogrammetric Engineering and remote sensing, 57(3), 295-303.

[11] Aiazzi, B., Baronti, S., & Selva, M. (2007). Improving component substitution pansharpening through multivariate regression of MS $+ $ Pan data. IEEE Transactions on Geoscience and Remote Sensing, 45(10), 3230-3239.

[12] Kahraman, S., & Ertürk, A. (2018). Review and Performance Comparison of Pansharpening Algorithms for RASAT Images. Electrica, 18(1), 109-120.

[13] Gungor, O., & Shan, J. (2004, July). Evaluation of satellite image fusion using wavelet transform. In proceedings of 20th Congress ISPRS "Geo-Imagery Bridging Continents (pp. 12-13).

[14] Witharana, C., Civco, D. L., & Meyer, T. H. (2013). Evaluation of pansharpening algorithms in support of earth observation based rapid-mapping workflows. Applied Geography, 37, 63-87.

[15] Vekkot, S., & Shukla, P. (2009). A novel architecture for wavelet based image fusion. World Academy of Science, Engineering and Technology, 57, 372-377.

[16] Panchal, S., & Thakker, R. (2015). Implementation and comparative quantitative assessment of different multispectral image pansharpening approches.arXiv preprint arXiv:1511.04659.

[17] Liu, P. C. (1994). Wavelet spectrum analysis and ocean wind waves. In Wavelet Analysis and Its Applications (Vol. 4, pp. 151-166). Academic Press.

[18] Ma, H., Jia, C., & Liu, S. (2005). Multisource image fusion based on wavelet transform. International Journal of Information Technology, 11(7), 81-91.

[19] Pajares, G., & De La Cruz, J. M. (2004). A wavelet-based image fusion tutorial. Pattern recognition, 37(9), 1855-1872.

[20] Pohl, C., & Van Genderen, J. L. (1998). Review article multisensor image fusion in remote sensing: concepts, methods and applications. International journal of remote sensing, 19(5), 823-854.

[21] Hill, P. R., Canagarajah, C. N., & Bull, D. R. (2002, September). Image Fusion Using Complex Wavelets. In BMVC (pp. 1-10).

[22] Shensa, M. J. (1992). The discrete wavelet transform: wedding the a trous and Mallat algorithms. IEEE Transactions on signal processing, 40(10), 2464-2482.

[23] Stathaki, T. (2011). Image fusion: algorithms and applications. Elsevier.

[24] Ward, D. L. (2003). Redundant discrete wavelet transform based super-resolution using sub-pixel image registration (No. AFIT/GE/ENG/03-18). AIR FORCE INST OF TECH WRIGHT-PATTERSON AFB OH SCHOOL OF ENGINEERING AND MANAGEMENT.

[25] Hill, P. R., Canagarajah, C. N., & Bull, D. R. (2002, September). Image Fusion Using Complex Wavelets. In BMVC (pp. 1-10).

[26] Sankar, V. (2018). Projector Compensation for Unconventional Projection Surface (Master's thesis, University of Waterloo).

[27] Udomhunsakul, S., Yamsang, P., Tumthong, S., & Borwonwatanadelok, P. (2011). Multiresolution edge fusion using swt and sfm. In Proceedings of the World Congress on Engineering (Vol. 2, pp. 6-8).

[28] Zhang, J. (2017). Christine Pohl and John van Genderen, Remote sensing image fusion-a practical guide.

[29] Yakhdani, M. F., & Azizi, A. (2010). Quality assessment of image fusion techniques for multisensor high resolution satellite images (case study: IRS-P5 and IRS-P6 satellite images). na.

[30] Sruthy, S., Parameswaran, L., & Sasi, A. P. (2013, March). Image fusion technique using DT-CWT. In 2013 International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s) (pp. 160-164). IEEE.

[31] Yadav, N., & Shrivastri, S. (2014). A review of image fusion using ihs with wavelet transform. International Journal of Computer Science Trends and Technology, 2(6), 15-20.

[32] Jinju, J., Santhi, N., Ramar, K., & Bama, B. S. (2019). Spatial frequency discrete wavelet transform image fusion technique for remote sensing applications. Engineering Science and Technology, an International Journal.

[33] Paramanandham, N., & Rajendiran, K. (2018). Multi sensor image fusion for surveillance applications using hybrid image fusion algorithm. Multimedia Tools and Applications, 1-32.

[34] Boltižiar, M., & Chrastina, P. (2018). Application of Geographical Information System (GIS) in Geography (Digital Data Pre-processing for Land-use Changes Analysis). DIVAI 2018.

[35] Selva, M., Santurri, L., & Baronti, S. (2018). On the use of the expanded image in quality assessment of pansharpened images. IEEE Geoscience and Remote Sensing Letters, 15(3), 320-324.

[36] Pandit, V. R., & Bhiwani, R. J. (2015). Image fusion in remote sensing applications: A review. International journal of computer applications, 120(10).